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Research Article

A Comparative Study in Forecasting Power Generation in Kuwait using Various Artificial Intelligence Models

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Abstract

Kuwait has a high demand for electricity towards indoor cooling and desalination of water, which it meets mainly through its fossil fuel reserves. The low energy tariffs and the carefree consumption have led to noticeably high per capita CO_2 emissions, and it has faced around 2 degrees rise in temperatures over the decades. To meet its power requirements and combat emissions, investments towards the development of renewable sources of energy has taken the front seat, which require reliable forecasting techniques to lay the roadmap for future action. Though multiple sources are on offer in the energy market and for decades such a choice was absent, it is reasonable to go a step further to ensure that every household gets the optimum energy mix both in terms of minimal costs and minimal carbon emissions. Thus, power management units are incorporated on supply lines to dynamically manage the allocation of power from multiple sources when the supply and demand both are variable. This work discusses the popular algorithms associated with the forecasting and prediction of power generation in this field, and dynamic allocation of units to the consumers as the supply from these sources varies.

Keywords: *Power Generation, CO_2 emissions etc.*

Introduction

Dawlat al-Kuwayt, or Kuwait, is in one of the driest, least hospitable deserts on Earth. It has no permanent sources of surface water and is thus dependent on desalination or groundwater to meet its freshwater demands. Agriculture is limited to some fertile patches. The huge oil reserves are what has made this nation wealthy. Temperatures higher than 50 degrees Celsius are not unheard of and such high temperatures can last for several consecutive days, and nearly two-thirds of domestic power consumption is towards air conditioning (Zafar, 2023). This also makes Kuwait have one of the highest per capita emissions of CO_2 in the world. In the words of Abraham Verghese, a physician, author, and professor, "Geography is destiny," and it can be unforgiving at times. Though the inhabitants have braved the harsh climate and erratic sandstorms for centuries, (Christofaro, 2022; Zafar, 2023) note the noticeable rise in temperatures as the Kuwaiti climate becomes lethal for the terrestrial flora and fauna, the marine life, as well as the huge migrant population which works outdoors in such conditions. For the countries in the Gulf Cooperation Council (GCC), of which Kuwait is a member, domestic per capita power consumption is high. Kuwait faces dual problems of declining fossil fuel reserves and high carbon emissions. (Al-Badi and AlMubarak, 2019) recommends the adoption of renewable sources of energy, wind and solar, to meet the rising power demand while cutting down on the emissions and their consequences on the local climate.

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Shagaya Renewable Energy Park

The Shagaya Renewable Energy Park project (Steensma *et al*, 2019), initiated by the Kuwait Institute for Scientific Research (KISR), is unfolding in phases, installing Concentrated Solar Power Plant(s), Solar Photovoltaic (PV) Plant(s) and Wind Farm(s), with a vision to generate 15 percent of the Kuwait's projected power demand in 2030 (Al-Badi and AlMubarak, 2019). It has designed and developed through collaboration with international consultants, thus benefitting from their expertise with numerous other projects in other regions. The official opening happened in the February of 2019.

Unique Challenges posed by the Kuwaiti Climate.

The harsh environment of Kuwait necessitates the continuous monitoring of the equipment for repair and maintenance, which presents another arena where machine learning models can be of great assistance.

Though the geographical location of Kuwait receives ample solar radiation, (Al-Dousari, *et al*, 2019) find that a high count of dusty days in a year, erratic sandstorms, and humidity, cause deposition of crust like layers of the open surfaces of solar panels, which significantly decreases their generation efficiency and raises the risk of surficial damage to the panels during maintenance. The spatial distribution of such dust zones is generally a determinant in positioning of solar farms. Wind turbines also get affected by dust accumulation during sandstorms, though it does not pose a problem of the same magnitude. With an elderly population attributing climate change to the will of God and resisting lifestyle changes, a shift towards renewables is more than a matter of political will and financial capability. For an economy primarily flourishing on the processing and consumption of fossil fuels, renewables pose obvious concerns (Alsayegh, 2021).

Dynamic Systems for Optimum Energy Mix

Rapid urbanization in Kuwait has provided impetus to the planning and development of smart cities such as XZero (Florian, 2022), an essential component being the installation of smart grids. Smart grids enable two -way communication between the consumer and provider to ensure synchrony between power demand and power supply at reduced costs, improved security, and better management of load during peak hours. As the power generated from wind and solar are intermittently available irrespective of the nature and magnitude of the load, the concept of power management unit between the sources and the load has been explored by several researchers. The basic idea is to have a dynamic controller which can compensate the supply from an alternative source, when the supply from the active one goes low, or the active one becomes pricier.

Usefulness of Predictive Technology in Energy Sector

Archeological excavations in and around Kuwait Bay find indicate that fishes were part of the local diet. Besides commercial and recreational fishing, maritime trading has been another important economic activity. For fishermen and seafarers to leave the safety of the land and sail towards the deep sea, the ability to foretell the weather was and is a celebrated skill. The energy sector has not shied away from technology which can assist that.

Forecasting and predictive machine learning techniques

To the energy sector, forecasts of demand and supply, both of which are affected by the weather besides numerous other factors, are of great business value. Such forecasts can be required as part of the government regulations. They prepare the industry for the continually rising aggregate consumption and facilitate the diversion of available supply towards public utilities, like hospitals, in the event of an unforeseen power crisis. For dynamic allocation of units, a day ahead forecast is needed, which is categorized as short-term forecasts. The IEEE Working Group on Energy Forecasting (WGEF) organized the Global Energy Forecasting Competition (GEFCom2012) in 2012 (Hong, Pinson and Fan, 2014), GEFCom2014 in 2014 (Hong, Pinson, Fan, Zareipour, Troccoli and Hyndman, 2016) and then in GEFCom2017 in 2017 (Hong, Xie and Black, 2019), to propel research in this field.

As wind speed and solar radiation are dependent on meteorological phenomena, numerical weather prediction (NWP) models generate a vast majority of such day ahead forecasts. A set of seven partial differential equations with seven unknowns obtained from the law of conservation of momentum, the law of conservation of mass, the equation of state for ideal gases, the first law of thermodynamics or conservation of energy, and a conservation equation for water mass, forms the universal basis for NWP Models. There are decades of research backing these equations and supercomputers of the respective decades have been employed to grid the region under study and apply numerical methods to solve the equations by gridding the atmosphere (Pu and Kalnay, 2019). Equations (1)-(10) elaborate the NWP model.

$$u = r\cos\varphi\frac{d\lambda}{dt} \tag{1}$$

$$v = r\frac{d\varphi}{dt} \tag{2}$$

$$w = \frac{dr}{dt} \tag{3}$$

$$\frac{\partial u}{\partial t} = -u\frac{\partial u}{\partial x} - v\frac{\partial u}{\partial y} - w\frac{\partial u}{\partial z} + \frac{uv\tan\phi}{a} - \frac{uw}{a} - \frac{1}{p}\frac{\partial p}{\partial x} - 2\Omega(w\cos\phi - v\sin\phi) + Fr_x \tag{4}$$

$$\frac{\partial v}{\partial t} = -u\frac{\partial v}{\partial x} - v\frac{\partial v}{\partial y} - w\frac{\partial v}{\partial z} - \frac{u^2\tan\phi}{a} - \frac{uw}{a} - \frac{1}{\rho}\frac{\partial \rho}{\partial y} - 2\Omega u\sin\phi + Fr_y \tag{5}$$

$$\frac{\partial w}{\partial t} = -u\frac{\partial w}{\partial x} - v\frac{\partial w}{\partial y} - w\frac{\partial w}{\partial z} - \frac{u^2+v^2}{a} - \frac{1}{\rho}\frac{\partial \rho}{\partial z} - 2\Omega u\cos\phi + Fr_z \tag{6}$$

$$\frac{\partial T}{\partial t} = -u\frac{\partial T}{\partial x} - v\frac{\partial T}{\partial y} + (\gamma - \gamma_d)w + \frac{1}{c_\rho}\frac{dH}{dt} \tag{7}$$

$$\frac{\partial \rho}{\partial t} = -u\frac{\partial p}{\partial x} - v\frac{\partial \rho}{\partial y} - w\frac{\partial \rho}{\partial z} - \rho(\frac{\partial u}{\partial x} + \frac{\partial u}{\partial y} + \frac{\partial w}{\partial z}) \tag{8}$$

$$\frac{\partial q_v}{\partial x} = -u\frac{\partial q_v}{\partial x} - v\frac{\partial q_v}{\partial y} - w\frac{\partial q_v}{\partial w} + Q_v \tag{9}$$

$$p\alpha = RT \tag{10}$$

where,
t represents an arbitrary time,
α represents specific volume,
ρ represents density,
p represents pressure,
T represents temperature,
λ represents the longitude of the location,
ϕ represents the latitude of the location,
r represents the radius of the Earth,
q represents the water vapor mixing ratio,
Q is heating,

F represents the friction force,
γ represents lapse rate,
γ_d represents dry lapse rate,
R is the universal gas constant=8.314 L/mol-K.

With increase in computing power and availability of inexpensive memory devices, machine learning algorithms have found widespread popularity in all industries and complement the NWP models with additional insights. (Markovics and Mayer, 2022) train a multitude of machine learning models of different types on the same NWP generated data to compare their performances, and concluded some models can deliver impressive results.

Regression Models

Across the GEFCom2012 (Hong, Pinson and Fan, 2014), GEFCom2014 (Hong, Pinson, Fan, Zareipour, Troccoli and Hyndman, 2016), and GEFCom2017 (Hong, Xie and Black, 2019), it was observed that most of the qualifying teams were employing quantile regression, multiple linear regression, decision trees et cetera. Thus, this section discusses some common regression models.

Multiple Linear Regression (MLR)

The method of MLR estimates the parameters of Equation (11), where x's represent the independent variables or predictors, and y represents the outcome variable or predictand. Though the least square method is more commonly used to estimate the parameters, robust regression is a better alternative, which iteratively reassesses the weights assigned to each predictor to minimize the effect of potential outliers.

$$y_i = \beta_0 + \sum_k \beta_k x_{ki} + \epsilon_i \quad (11)$$

(Mas' ud, 2022) uses global horizontal irradiance (GHI) and PV cell temperature measured in the Jubail Industrial City in Saudi Arabia, to determine the PV output. It is found that GHI increases the PV output while higher temperatures have a detrimental effect.

K Nearest Neighbors

In this method, to estimate the outcome of the datapoint under study, the outcomes of "k" most similar/nearest points are averaged, where k is a parameter decided by the analyst. The similarity is evaluated using common distance measures such as the Euclidean distance, calculated as in Equation (12).

$$d_{12} = \sqrt[2]{\sum_{i=1}^{i=N} (x_{1i} - x_{2i})^2} \quad (12)$$

As (Mas' ud, 2022) mentions, the simplicity and intuitiveness in this method make it popular, however, for large datasets, calculating the distance matrix poses high memory requirements.

Decision Tree Regression

The decision tree algorithm uses measures of information gain, such as Entropy or Gini Index, to partition the dataset into blocks and sub-blocks into a flowchart like structure, comprising of branches, nodes, and leaves. The objective is to partition the scenarios presented in the training dataset into similar groups within given parameterized constraints. For a given combination of predictors, the branches in the flowchart identify the suitable leaf and the outcome variable is determined by the average of that group. As mentioned in (Mas' ud, 2022), decision trees are capable of modelling non-linearities in the data in limited computation time. It is common to use multiple decision trees trained on different subsets of the same dataset, and assimilate their individual result for the outcome. This is called random forest (Hong, Xie, and Black, 2019), which is not just a popular algorithm, but outdoes other advanced techniques in several scenarios.

The M4 competition (Makridakis, Spiliotis and Assimakopoulos, 2020) in 2018 sought the participation of researchers and analysts to raise the bar in the field of time series forecasting models over a variety of time series. The statistical model, deep learning models and their ensembles were found to be good performers.

Classical timeseries forecasting models owe their popularity to their simplicity and ease of implementation irrespective of the domain of study.

Naive. The naïve method assigns the value of the latest measurement to the forecast for the next instant. It is expressed in Equation (13),

$$\hat{y}_{t+h} = y_t \quad (13)$$

It is common to use the naive method as a baseline for whatever models are developed/used. Variations of this technique can be used for data with seasonal components, as well as seasonally adjusted data.

Holt Winters Model

The Holt–Winters model consists of a forecast equation and smoothing equations of the level, trend, and seasonality of the time series. It falls under the umbrella of Exponential Smoothing Models. This has been employed by (Almazrouee, Almeshal, Almutairi, Alenezi and Alhajeri, 2020) for modelling the peak loads in Kuwait over a 10-year period, thus suggesting the low periods which can be devoted to maintenance without disrupting daily lives. The model is represented by Equations (14)-(17) (Shah and Dimitrov, 2022).

$$Level: l_t = \alpha \left(\frac{x_t}{s_{t-S}}\right) + (1-\alpha)(l_{t-1} + b_{t-1}) \quad (14)$$

$$Trend: b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{15}$$

$$Seasonal: s_t = \gamma\left(\frac{x_t}{l_{t-1}+b_{t-1}}\right) + (1-\gamma)s_{t-S} \tag{16}$$

$$Forecast: \hat{y}_{t+m|t} = (l_t + b_t m)s_{t+m-S} \tag{17}$$

Autoregressive Integrated Moving Average (ARIMA)

Stationarity in a time series implies time invariance of statistical properties like mean and variance. When data is stationary, autoregressive (AR) and moving averages (MA), and their combination (ARMA) models have been used.

Equation (18) is the mathematical representation of the ARMA model

$$(1 - \sum_{i=1}^{p} \alpha_i L^i)X_t = (1 - \theta_i L^i)\varepsilon_t \tag{18}$$

However, real time series are mostly non-stationary. Therefore, as per the Box Jenkins methodology, ARIMA models, Equation (19), are built which incorporate the differencing of the time series to make it stationary.

$$(1 - \sum_{i=1}^{p} \alpha_i L^i)(1-L)^d X_t = (1 - \sum_{j=1}^{p} \theta_i L^i)\varepsilon_t \tag{19}$$

A SARIMA model, Equation (20), adds seasonality to a generic ARIMA model.

$$(1 - \sum_{i=1}^{p} \alpha_i L^i)(1 - \sum_{j=1}^{P} \square_j (L^S)^j)(1-L)^d(1 - L^S)^D X_t = (1 - \sum_{j=1}^{q} \theta_i L^i)(1 - \sum_{j=1}^{Q} \Theta_j (L^S)^j)\varepsilon_t \tag{20}$$

where, p = order of AR terms (non-seasonal),
P = order of AR terms (seasonal),
q = order of MA terms (non-seasonal),
Q = order of MA terms (seasonal),
d = order of differencing (non-seasonal),
D = order of differencing (seasonal),
S = span of pattern in seasonality

Prophet Model

Developed and used by Facebook for their analytics, Proph*et al*lows the inclusion of holidays and special events, besides trend and multiple seasonal patterns, thus facilitating the inclusion of domain knowledge into an otherwise statistical setup. This is relevant to the energy sector as onset of festivals/holidays can lead to unprecedented surge in demands. Prophet is an additive model, as seen in Equation (21),

$$y_t = b(t) + s(t) + f(t) + e_t \tag{21}$$

wherein, b(t) represents the non-periodic components modelled as linear and non-linear trends, s(t) represents the multiple periodicities, such as weekly, monthly, and quarterly, f(t) represents the contribution of calendar events which can impact the forecast as determined by the analyst, and e_t is the error term. (Almazrouee, Almeshal, Almutairi, Alenezi and Alhajeri, 2020) use a piecewise linear growth function for the Prophet model, defined in Equation (22).

$$b(t) = (k + a(t)^T\delta)t + (m + a(t)^T\gamma) \tag{22}$$

where,
k=growth rate,
δ=adjustment rate,
m=offset parameter,
γ=points where the trend changes,
a(t) is 1 for periods following the change of trend, 0 otherwise.

Daily, weekly, and yearly seasonality is modelled using a composite Fourier series.

TBATS

TBATS combines trigonometric seasonality, Box-Cox transformations, ARMA errors, trend, and seasonal components to derive its name. The combination of multiple features which have been celebrated in the domain of time series forecasting makes it an especially useful model when the time series demonstrates seasonal patterns with multiple and/or fractional periods (Brozyna, Mentel, Szetela and Strielkowski, 2018) which and/or correspond to non-standard calendars like those based on lunar cycles (De Livera, Hyndman and Snyder, 2011). Equations (23)-(28) show the mathematical representation of this model.

$$y_t^{(\omega)} = l_{t-1} + \varphi b_{t-1} + \sum_{i=1}^{T} s_{t-1}^{(i)} + \alpha d_t \tag{23}$$

$$b_t = b_{t-1} + \beta d_t \tag{24}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{25}$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos\lambda_j^{(i)} + s_{j,t-1}^{*} \sin\lambda_j^{(i)} + \gamma_1^{(i)} d_t \tag{26}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1}^{(i)} \sin\lambda_j^{(i)} + s_{j,t-1}^{*(i)} \cos\lambda_j^{(i)} + \gamma_2^{(i)} d_t \tag{27}$$

$$\lambda_j^{(i)} = \frac{2\pi j}{m_i} \tag{28}$$

where,
i is an integer value from 1 to T,
d_t represents an ARMA(p,q) process with p autoregressive terms and q moving average terms,
α, β, γ_1, γ_2 represent the smoothing parameters,
l_0 is the initial level,
b_0 is the slope.

The Python and R implementations of TBATS fit multiple models to the data and pick the one with the best performance assessed by a low Akaike Information Criteria (AIC) value.

Artificial Neural Networks (ANNs)

ANNs are structurally represented by a set of interconnected layers, each composed of a finite count of blocks referred to as neurons, represented mathematically by Equation (29). It can be visualized as a sandwich of several layers, often with different characteristics.

$$y = f(\sum_1^n w_i A_i + b) \tag{29}$$

where y is the output of the neuron, and w_i represents the weight assigned to synapses(linkages), which carry inputs A_i. b is the bias. f(x) is the transfer function. The process of training these models essentially involves the tuning of the weights and biases to get the desired outputs. Sigmoid and Gaussian, presented here in Equations (30)-(31), are some of the common transfer functions.

Sigmoid function:

$$f(x) = \frac{1}{1+e^{-x}} \tag{30}$$

Gaussian function:

$$f(x) = e^{-x^2} \tag{31}$$

Weather prediction and climate modelling, and associated forecasts in the energy sector, have been attempted with data mining tools and ANNs ever since their inception, however, as (Schultz *et al*, 2021) reports, these have been mostly simple models with limited resources which failed to propel research in this direction. Besides the black box nature of ANNs and requirement of large training datasets, complex characteristics of meteorological phenomena like cyclical nature and interrelations between outcome variables like humidity, pressure, temperature et cetera has deterred the application of ANNs in this domain. Yet, with recent developments, such systems are improving and adding value to NWP forecasts. Customizing of the transfer functions and, transfer learning et cetera can make ANNs suitable for generating reliable forecast. (Chen, Birkelund, Anfinsen, Staupe-Delgado & Yuan, 2021) find the best probability distributions for observed wind speeds and NWP generated wind speeds recorded across five Norwegian wind farms in the Arctic region. Similar distributions are fit using transposition methods for solar irradiation in (Quan and Yang, 2020). Such distributions can be included in these ANNs using the Bayesian approach.

Performance Evaluation

The goodness of any predictive model/technique is assessed using a multitude of metrics, a few of those presented here in Equations (32)-(35): Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), nRMSE is the RMSE normalized to the nominal capacity of the PV system.

$$MAE = \frac{1}{h}\sum_{i=1}^{h} |y_t - \widehat{y_t}| \tag{32}$$

$$MAPE = \frac{1}{h}\sum_{i=1}^{h} \frac{|y_t - \widehat{y_t}|}{y_t} \times 100 \tag{33}$$

$$RMSE = \sqrt[2]{\frac{1}{h}\sum_{t=1}^{h}(y_t - \widehat{y_t})^2} \tag{34}$$

$$nRMSE = \frac{100}{P_n} \times \sqrt[2]{\frac{1}{h} \times \sum_{t=1}^{h}(y_t - \widehat{y_t})^2} \tag{35}$$

GEFCom2014 (Hong, Pinson, Fan, Zareipour, Troccoli and Hyndman, 2016) required the participants to submit their forecasts in the form of quantiles. For a quantile forecast, the metric is as mentioned in Equation (36) was used.

$$L(q_a, y) = \begin{cases} \left(1 - \frac{a}{100}\right)(q_a - y), if\ y < q_a \\ \frac{a}{100}(y - q_a), if\ y \geq q_a \end{cases} \tag{36}$$

where y is the actual value,
q_a is the quantile forecast,
a/100 represents the target quantile.

Across literature, myriad other metrics have been used. No one metric is the perfect for all scenarios, thus a set of metrics are used together to assess the quality of the forecasts. Lower the metrics, better is the model.

Optimization techniques for power unit management

The objective of a power management unit is to optimally allocate the number of units sourced from each source of energy such that multiple objectives, such as lowest monetary cost and lowest carbon emissions, while fulfilling the lead requirements of the consumer. Such controllers work with a multitude of bio-inspired optimization algorithms like particle swarm optimization, or search strategies like hill climbing, or the mixed-integer linear programming model, to find the optimum low-cost solutions. Rule-based mechanical power switching systems are not new and have been in commercial usage for decades, but intelligent automated switching is gaining momentum in research. (An and Tuan, 2018) contrasts the performance of a rule-based system to the performance of a dynamic programming system for a hybrid network with three sources: diesel, wind and solar, serving AC load, and storing the surplus in a battery. If the demand exceeds the supply, the battery discharges to balance the demand.

(Liu, Xu, Wei and Liu, 2017) present a system wherein each residence connected to the grid has a solar panel. The power generated by these panels gets used for the residential load, charging a battery, and excess transmitted to the grid for distribution towards public utilities. If the panel does not generate enough, the residence can draw power from the grid. Action dependent heuristic dynamic programming (ADHDP) method determines the when and how much energy should be transferred to the grid, when and how much to store in batteries, and when and how much to draw from the grid, based on the costs associated with the transactions. The solar output is categorized based on the cloud cover. A penalty term is added to the optimization model, to encourage certain choices among the consumers. Several simulation, optimization and investment support software packages are available and widely used across the world, a review of such tools is presented in (Ringkjøb, Haugan and Solbrekke, 2018). (Ani, 2021) uses HOMER and (Kumar, 2017) uses GAMS for optimization of similar systems.

Material and methods

Data. A simulation data inspired by (Open Power System Data, 2020) is used for this demonstration. It contains columns for the load, power generated by wind and solar, and the price of renewable energy forecasted a day ahead for each hour from midnight 25th of October 2015 till 2300hrs of 31st of December, 2016.

Software. Python is rapidly becoming the programming language of choice across academia and industry. It is supported by numerous libraries for scientific computation, an example being Pymoo (Blank and Deb, 2020). However, simplicity is key to reliability. The problem is formulated as a Single Objective Linear Programming (LP) solved using PuLP (Kapić and Kulenović, 2019). LP is a popular technique in the field of operations research, applied to myriad problems like resource allocation, task scheduling, and transportation.

For the day ahead forecasting, the statistical software tool R is used. The implementation of TBATS (De Livera, Hyndman and Snyder, 2011) in the forecast package is used. The data is split into training and testing, with daily, weekly, and monthly seasonalities used to model the time series.

Results

Figure 1 shows the hourly loads for the fictious city, the seasonality on an hourly and quarterly basis is visible. There is a sharp dip in the month of January. Figure 2 shows the hourly generation of solar power. As this fictious city is in the Northern Hemisphere, longer days from March to October cause the output to rise. Figure 3 shows the 300 hours output of solar power, a subset of the series in Figure 2. It can be seen how the generation rises, peaks and dips during the day with no output at night, giving the look of consecutive pyramids. Figure 4 shows the time series of power generated through wind. Summer months record lower output; however, any seasonality is not obvious from the graph. Figure 5 shows the day ahead price of one kW of renewable power. In contrast to the fluctuating prices, conventional grid power has been priced at 25 Euro/kW for this project. An additional amount has been added as penalty per unit with the intent of discouraging the optimization from favoring grid power owing to low tariffs. When solar power is available, this penalty is 100, when solar power is not available, it is 25.

The LP is formulated as a minimization problem, and the optimization is done iteratively for each hour. The units allocated to each source of energy are the unknowns in this formulation. The supply, demand and costs are fetched from the dataset. The mathematical representation is as follows:

Minimize:

$$Cost = DAP_{Solar} * Units_{Solar} + DAP_{Wind} * Units_{Wind} + Units_{Grid} * (25 + penalty)$$

Subject to constraints:

$$Units_{Solar} + Units_{Wind} + Units_{Grid} \geq Demand$$
$$Units_{Solar}, Units_{Wind}, Units_{Grid} \geq 0$$
$$Units_{Solar} \leq Supply_{Solar}$$
$$Units_{Wind} \leq Supply_{Wind}$$
$$Units_{Grid} \leq Supply_{Grid}$$

The units corresponding to each hour are presented in Figure 6, it can be observed that the intermittent nature of renewables leaves a high dependence on grid power. It dips in the months of March to October as solar generation increases in these months.

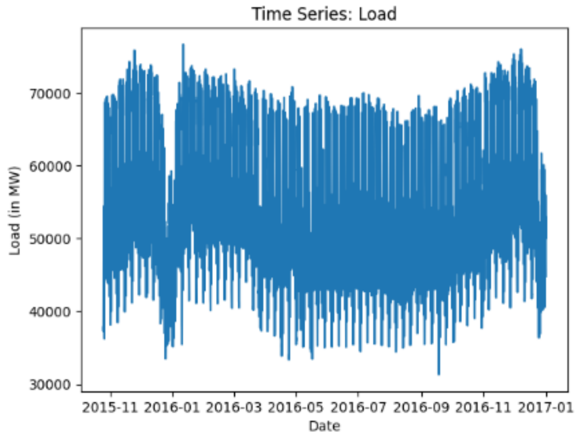

Figure 1. Time Series: Load in MW

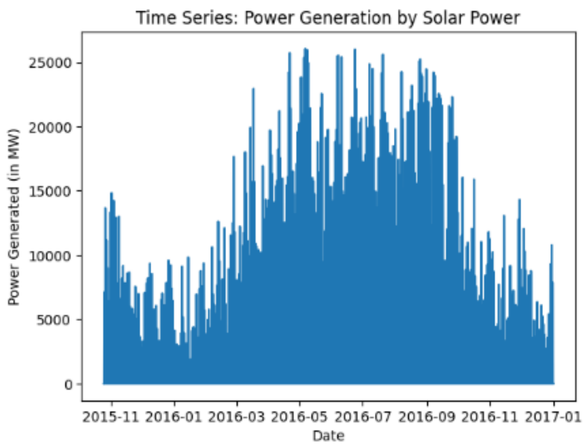

Figure 2. Time Series: Power generated by Solar Energy

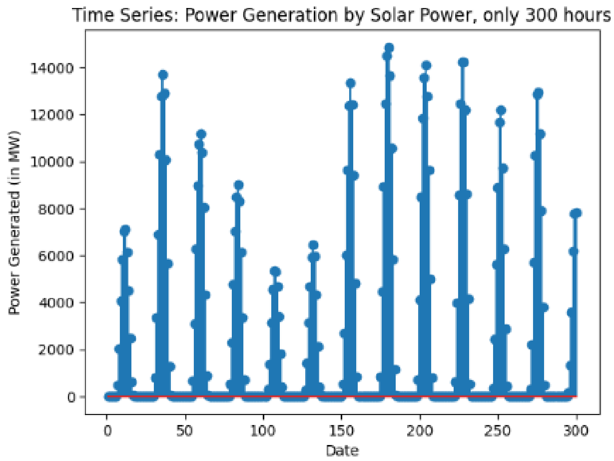

Figure 3. Time Series: 300 hours of solar output

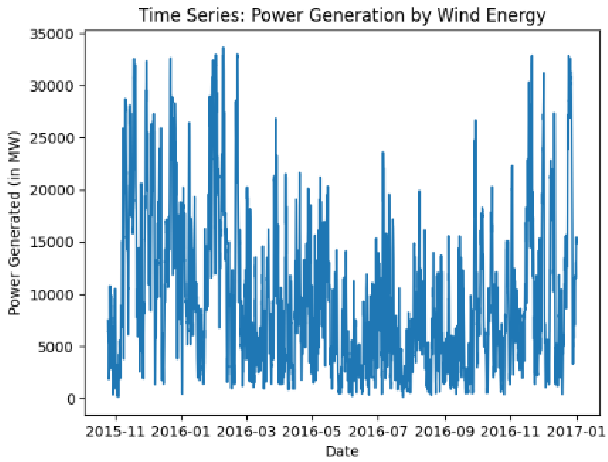

Figure 4. Time Series: Power Generation by Wind Energy

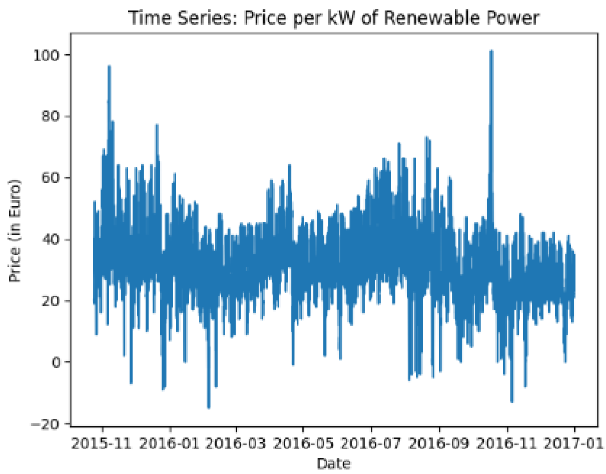

Figure 5. Time Series: Price per kW of renewable energy

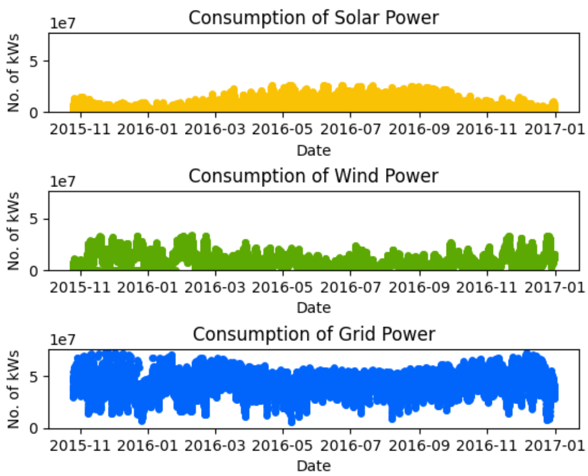

Figure 6. Consumption of Solar, Wind and Grid, as determined by LP

The TBATS model is used to forecast the load it demonstrates seasonality at daily, weekly, and monthly levels. The forecast is presented in Figure 7 in blue color. The grey region indicates the 80% and 95% confidence intervals of these forecasted values. This model reports a MAPE (Equation 33) of 12 percent.

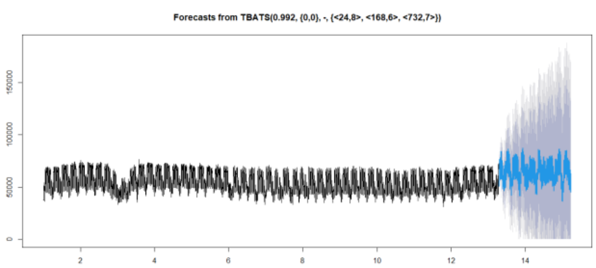

Figure 7. TBATS Forecast of load

Future Work

In (Chen, Zhang, Dong, Huang, Guo, and He, 2021), instead of forecasting the aggregate output of the wind farm, uses a network of Long Short-Term Memory (LSTM) models followed by a Convolutional Neural Network model (CNN), such that LSTM captures the temporal variations and CNN the spatial ones, and generate forecasts for individual turbines. This model is visually observed to closely follow the real power generated.

The problem statement in GEFCom2017 (Hong, Xie and Black, 2019) required contestants to forecast the power consumption of 100 delivery point meters organized into a hierarchy of spatial zones. The data was sourced from an anonymous provider.

As accurate forecasting at both supply and demand sides is in the spotlight, it inspires the possibility of developing a prediction cum optimization system which can add value to such a smart grid, with an implementation like the one presented in (Chen, Zhang, Dong, Huang, Guo and He, 2021).

The optimization demonstrated here uses the total load of the city, thus it fails to capture variations in load in different parts of the city, say facilities in tourist locations might draw more power. Instead of aggregate, this fictious city can be modelled considering the load of different entities, such as residences, commercial spaces, public utility like a train station et cetera to get a more realistic estimate of the allocation of units. Such entities generally pay different energy tariffs, and public utility like a hospital should be ensured 24hrs uninterrupted power supply even in an energy crisis. The inclusion of dynamic tariffs, priority and in the context of Kuwait can greatly alter the optimum energy mix, and real time data from Kuwaiti consumers can make for an interesting study.

Conclusion

As fossil fuel reserves are dwindling and the ongoing climate change some unprecedented lemons with droughts, floods, untimely snowstorms et cetera, Kuwait is preparing for a sustainable future with cleaner, greener sources of energy and has embraced technological developments as it races closer to its goal. This work discusses the techniques used in forecasting and prediction of demand and supply as well as optimization techniques to determine the right energy mix to save on cost and emissions. The availability of simulation software packages/libraries facilitates the study of commercially relevant technologies and propels innovative ideas.

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